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Optimal distributed renewable generation planning: A review of different approaches

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ABSTRACT

Distributed generation has gained a lot of attractions in the power sector due to its ability in power loss reduction, increased reliability, low investment cost, and most significantly, to exploit renewable-energy resources, which produce power with minimum greenhouse-gas emissions like wind, photovoltaic and micro turbines. Installation of distributed generation at non-optimal location can result in various problems such as an increase in system losses and costs, voltage rise and fluctuations, reliability and stability problems. Therefore, it is necessary to develop an optimization or heuristic technique based methodology to identify the optimal placement of distributed renewable generation for a given system that can provide economic, environmental and technical advantages. There are several researches that study on the optimal distributed renewable generation location by their imposed constraints and objectives. However, the systematic principle for this issue is still an unsolved problem. This paper reviews some of the most popular distributed renewable generation placement methods, including 2/3 Rule, Analytical Methods, Optimal Power Flow, Mixed Integer Nonlinear Programming, various types of Artificial Intelligent optimization techniques and Hybrid Intelligent System. Each methodology has its own features and potential for significantly promote the applicability of distributed renewable generation in power systems.

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1. Introduction

One of the most important attractions for the studies on the integration of distributed resources to the grid is the exploitation of the renewable resources, such as wind, solar, hydro, biomass, geothermal and ocean energy. The 'renewable' term is defined as primary, domestic and clean or inexhaustible energy resources [1]. They are naturally scattered around the world and also are smaller in size. Accordingly, these resources can only be tapped through integration into the distribution network by means of distributed generation (DG).

Although there is no consensus on the exact definition of DG, there are some significant attempts, in the literature [2,3], to define the concept. DG is any source of electric power of limited capacity, directly connected to the power system distribution network where it is consumed by the end users. Governments around the world strive to achieve ambitious targets of incorporating considerable amounts of distributed renewable generation (DRG) and combined heat and power (CHP) in response to the climate-change challenge and the need to enhance fuel diversity [4]. Fig. 1 shows the annual DRG capacities around the world, with estimated increasing from 6000 to 17,000 MW in 2009 to 2015 [5].

A multitude of recent events has created a new environment for the electric power infrastructure. They are listed as follows [6]:

(i) Deregulation of the electric utility industry and the ensuing break-up of the vertically integrated utility structure.
(ii) Public opposition to building new transmission lines on environmental grounds.
(iii) Keen public awareness of the environmental impacts of electric power generation.
(iv) Rapid increases in electric power demand in certain regions of the country.
(v) Significant advances in several generation technologies that are much more environmentally benign (wind-electric generation, micro turbines, fuel cells, and photovoltaic) than conventional coal, oil, and gas-fired plants.
(vi) Increasing public desire to promote "green" technologies based on renewable-energy sources.
(vii) Awareness of the potential of DRG to enhance the security of electric power supply, especially to critical loads, by creating mini- and micro-grids in the case of emergencies and/or terrorist acts, and/or embargoes of energy supplies.

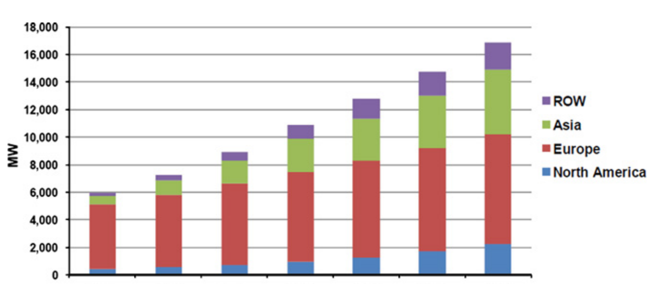

Fig. 1. Annual renewable distributed generation capacity additions, world markets: 2009–2015 [5].

Panvara et al. revealed that over the period from 1971 to 1995, CO_2 emissions grew at an average rate of 1.7% per year and had a faster growth rate, at 2.2% per year for the period towards 2020 [1]. Table 1 shows an overview of the most important emissions related to electricity production based on different technologies [7]. Ackermann et al. reviewed five renewable DG technologies in the power sector: hydro, wind, photovoltaic, geothermal and tidal power. This selection is fairly representative of technologies that are important in terms of their potential capacity to contribute to a low-carbon world economy. The data comprises direct emissions and indirect emissions. Indirect emissions are emissions that occur during the manufacturing of the power unit and the exploration and transport of the energy resources. Currently, only hydropower and wind power generate significant low-carbon portions of global electricity. Biomass is not included in the table, as it is considered CO_2 neutral, as the amount of CO_2 emitted into the atmosphere when biomass is burned is equal to the amount of CO_2 absorbed during its growth [7,8].

The DRG advantages can be best described by dividing them into three aspects, which are technical, economic and environmental. The technical advantages cover wide ranges of benefit such as efficiency, grid reinforcement, power loss reduction, reliability, eliminating or deferring the upgrades of the power system, improving load factors and voltage profile, thus increased power quality. The economic advantages include the reduction of transmission and distribution operating cost, reduced health care costs due to improved environment, saving the fossil-fuel cost and reduction on electricity tariff. Environmental advantages entail the reductions in emission of greenhouse gases (SO_2, CO_2), reducing sound pollution, and conservation of resources for additional use [9,10].

Despite its promises, installing the DRG into an electric power grid is not a simple plug-and-play problem. Indeed, as well as the operation of the DRG itself, it requires a careful consideration for the interaction with existing power network with respect to stability, reliability, protection coordination, power loss, power quality issues, etc. [11,12]. Installation of DRG at non-optimal places can result in an increase in system losses, reconfiguration of protection scheme, voltage rise and fluctuations, increase in costs, etc. It is necessary to develop proper methodologies and tools, which are capable of identifying the optimal location of DRG for a given system. These methodologies are based on the heuristic techniques or optimization programs [13].

This paper aims to review the techniques of DRG optimal location and sizing in power system environments, which summarized as shown in Fig. 2. In Section 2, the conventional algorithm of DRG placement methods is presented, which include the 2/3 Rule [14], Analytical Methods [15–20], Optimal Power Flow [21–29], and Mixed Integer Nonlinear Programming [30–33]. Section 3 reviews the Artificial Intelligent methods such

Table 1
Comparison of energy amortisation time and emissions of various distributed generation technologies [7].

Technology	Energy pay back time in months	SO_2 in kg/GWha	NO_x in kg/GWha	CO_2 in t/GWha	CO_2 and CO_2 equivalent for methane in t/GWh
Coal fired (pit)	1.0–1.1	630–1370	630–1560	830–920	1240
Nuclear	N.A	N.A	N.A	N.A	28–54
Gas (CCGT)	0.4	45–140	650–810	370–420	450
Large hydro	5–6	18–21	34–40	7–8	5
Renewable distributed generation technologies					
Micro hydro	9–11	38–46	71–86	16–20	N.A.
Small hydro	8–9	24–29	46–56	10–12	2
Wind turbine					
4.5 m/s	6–20	18–32	26–43	19–34	N.A.
5.5 m/s	4–13	13–20	18–27	13–22	N.A.
6.5 m/s	2–8	10–16	14–22	10–17	11
Photovoltaic					
Mono-crystalline	72–93	230–295	270–340	200–260	N.A.
Multi-crystalline	58–74	260–330	250–310	190–250	228
Amorphous	51–66	135–175	160–200	170–220	N.A.
Geothermal	N.A	N.A	N.A	N.A	50–70
Tidal	N.A	N.A	N.A	N.A	2

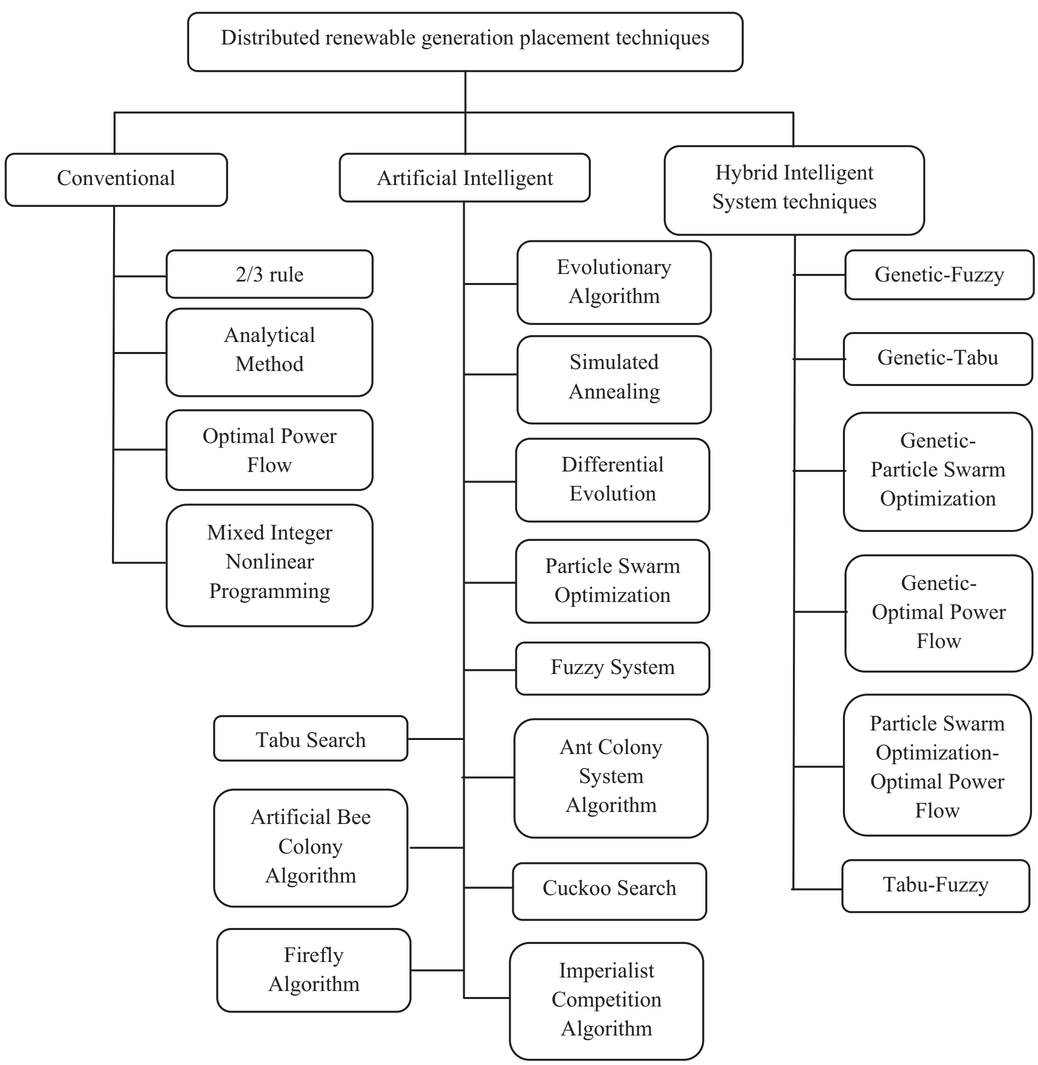

Fig. 2. Optimization placement techniques for DRG.

as the Evolutionary Algorithm [34–54], Simulated Annealing [55–57], Differential Evolution [58–63], Particle Swarm Optimization [64–70], Fuzzy System [71,72] and Tabu Search [73,74]. Section 4 presents possible promising techniques for future use in DRG placement such as the Ant Colony Search Algorithm [75,76], Artificial Bee Colony Algorithm [77–80], Cuckoo Search [81,82], Firefly Algorithm [83,84],

Imperialist Competition Algorithm [85–88], and various types of Hybrid System [89–98]. The conclusions are summarized in Section 5.

2. Conventional optimization techniques for distributed renewable generation placement

This section reviews the conventional optimal placement methods of DRG in power systems. These approaches vary according to their objectives such as to minimize power losses, minimize cost of systems, improve the voltage profile, increased the load ability and local marginal price. The mathematical algorithm, including the objective function, to solve the optimization-based DRG placement problem is discussed in this section.

2.1. 2/3 Rule

This rule is often used in proper placement of shunt capacitors in distribution systems. The 2/3 Rule proposes that the best capacitor size is 2/3 of the load which is located at 2/3 of the distance from the feeder. It also can be extended to "2/(2N+1)Rule" for N capacitors. For instance, the optimal locations for two units with approximately 2/5 capacity for each of them, might be located at the 2/5 and 4/5 length of the line [14].

This method is suitable for a radial feeder with uniformly distributed load, where it is suggested to install DRG of approximately 2/3 capacity of incoming generation at approximately 2/3 of the length of the line. It was proposed for minimizing the losses and voltage impacts and for feeders with uniform loads. Since it is a simple approximation, this technique cannot be applied directly to feeders or to distribution network systems with different types of loads such as increasing loads, centrally loads and other real systems with non-uniform loads.

2.2. Analytical Method

Various Analytical Methods (AM) have been proposed for the placement of DRG with optimal size in the distribution network. Most of the methods are based on theoretical, mathematical analysis and calculations [15–20]. They have common goals, which are to reduce the power losses, improve voltage profiles, finding optimal size and optimal location. Fig. 3. depicts the AM structure in solving the DRG planning problem.

In a work published in 2004, Wang and Nehrir [18] presented AM to determine the optimal location in radial as well as network systems to minimize the power loss of the system. To find the optimal location of DRG, the objective function (f_j) for DRG at bus j is as follows:

$$f_j=\sum_{i=1}^{j-1} R_{1i}(j)|S_{Li}|^2+\sum_{i=1}^{N} R_{1i}(j)|S_{Li}|^2, j=2,3,\ldots,N \tag{1}$$

where, $R_{1i}(j)$ is the equivalent resistance between bus 1 and bus i when DRG is located at bus$j$,$j\neq 1$. S_{Li} is complex power:

$$R_{1i}(j)=\begin{cases}\mathrm{Real}(Z_{11}+Z_{ii}-2Z_{1i}), & i<j\\ \mathrm{Real}\left(Z_{11}+Z_{(i-1)(i-1)}-2Z_{1(i-1)}\right), & i>j\end{cases} \tag{2}$$

where Z_{11}, Z_{ii}, Z_{1i} are the elements of impedance matrix.

When the DRG is located at bus 1 ($j=1$), the objective function will be as follows:

$$f_1=\sum_{i=1}^{N} R_{1i}(j)|S_{Li}|^2 \tag{3}$$

The goal is to find the optimal bus m where the objective function reaches its minimum value as follows:

$$f_m=Min\left(f_j\right),\ j=1,2,\ldots,N \tag{4}$$

The theoretical procedure to find the optimal bus to place DRG in a network system can be summarized as follows:

(i) Admittance matrix is calculated without DRG, then admittance matrix, impedance matrix, and equivalent resistances are calculated for different DRG locations.
(ii) Objective function values for DRG are calculated at different buses to find the optimal bus m.
(iii) If all the voltages were in an acceptable range when the DRG is located at bus m, then bus m is the optimal site.
(iv) If some bus voltages do not meet the voltage rule, then move the DRG around bus m to satisfy the voltage rule.
(v) If there is no bus that can satisfy the voltage regulation rule, then try a different size of DRG and repeat the procedure.

Acharya et al. [15] also proposed an analytical expression to calculate the DRG optimal size and placement for minimizing the total power losses in primary distribution systems. The objective function considers the total power loss (P_L), as shown in Eq. (5), where this expression is popularly known as "exact loss formula" in power systems [99]:

$$P_L=\sum_{i=1}^{N}\sum_{j=1}^{N}[\alpha_{ij}(P_iP_j+Q_iQ_j)+\beta_{ij}(P_iP_j-Q_iQ_j)] \tag{5}$$

where $\alpha_{ij}=r_{ij}/v_iv_j\cos(\delta_i-\delta_j)$, $\beta_{ij}=r_{ij}/v_iv_j\sin(\delta_i-\delta_j)$, $r_{ij}+x_{ij}=z_{ij}$ are the ijth element of bus impedance matrix (Z_{bus}), V_i, V_j are the voltages at ith and jth buses, respectively, P_i and P_j are the active power injection at the ith and jth bus, respectively, Q_i and Q_i are the reactive power injection at the ith and jth bus, respectively, N is number of buses, δ_i and δ_j are voltage phase angle at ith and jth buses, respectively.

Acharya et al. used the concept that approximates loss and actual loss calculated by utilizing the accurate load flow, following the same pattern. Using this concept, the load flow analysis required only two cycles, first time is by applying to the base case, and another time by applying with the DRG attached to obtain the final solution. The optimum size of DRG for each bus is calculated using Eq. (6), which is obtained by equating the rate of change of losses with respect to injected active power from DRG to bus ith to zero:

$$P_{DGi}=P_{Di}+\frac{1}{\alpha_{ii}}\left[\beta_{ii}Q_i-\sum_{j=1,j\neq i}^{N}\alpha_{ij}P_j-\beta_{ij}Q_j)\right] \tag{6}$$

where P_{DGi} is the real power injection from DRG placed at node i, and P_{Di} is the load demand at node i. Then, the approximate loss is computed for each bus by placing DRG with optimal size, one per time. The bus corresponding to minimum total loss will be the optimum location. After that the load flow analysis with DRG gives the final result; the exact loss.

In 2009, Gözel and Hocaoglu [16] formulated the problem using the expression for the total real loss (P_{loss}), to find the optimum location of DRG and was expressed as a function of the branch current injection:

$$P_{loss}=\sum_{i=1}^{nb}|B_i|^2\cdot R_i=[R]^T|[BIBC]\cdot[I]|^2 \tag{7}$$

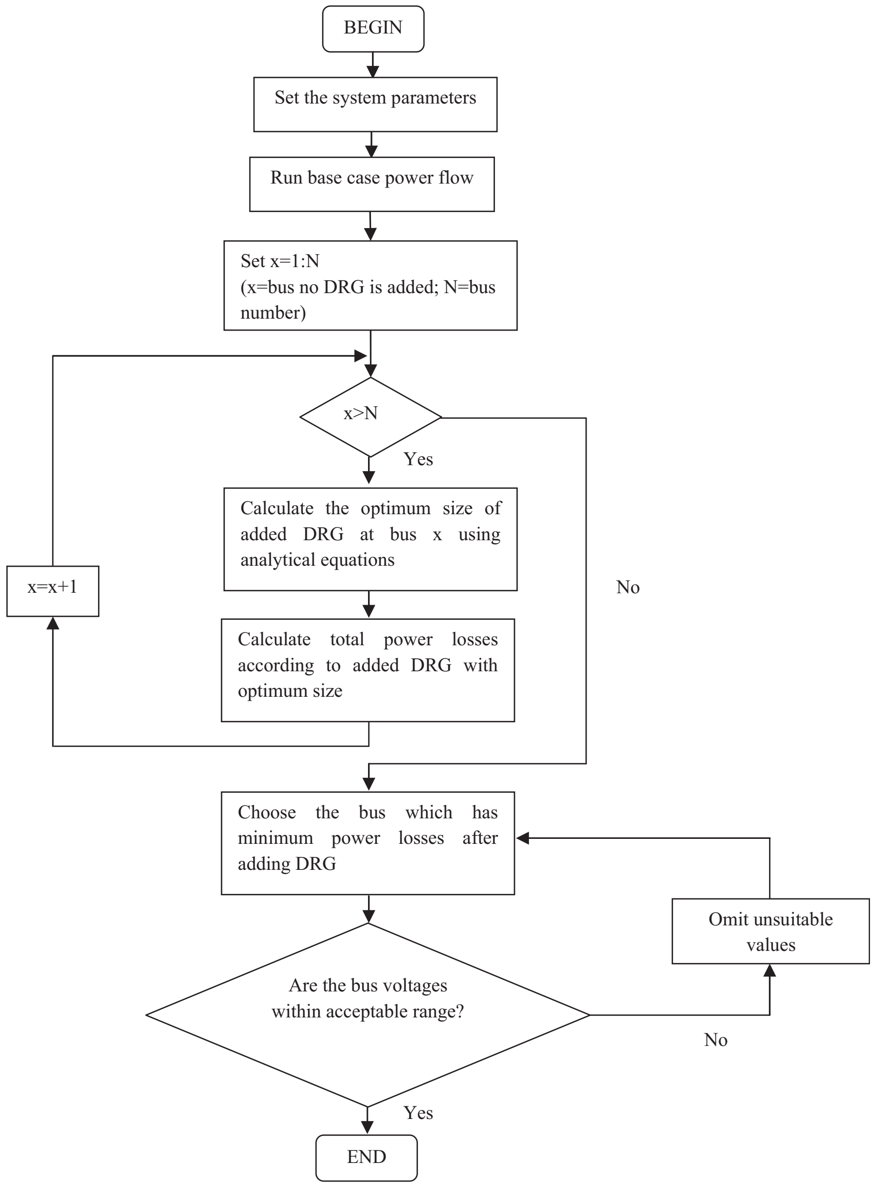

Fig. 3. Analytical Method flowchart [15–20].

where R_i is the ith branch resistance, $[R]$ is branch resistance row vector, nb is number of branches, $BIBC$ is bus-injection to branch-current matrix, and $[I]$ is the vector of the equivalent current injection for each bus except the reference bus.

The method is based on the equivalent current injection that uses the bus injection to branch current (BIBC) and branch current to bus voltage (BCBV) matrices, which were developed based on the topological structure of the distribution systems and is widely implemented for the load flow analysis of the distribution systems [100]. The proposed method requires only one base case load flow to determine the optimum size and location of DRG. The formula is derived as the derivative of the total power losses per each bus injected real powers, and equated to zero to determine the optimum size. The optimum size DRG is placed at each bus, and loss is calculated. The bus corresponding to minimum power loss will be defined as the optimum location, if the approximated bus voltages are within a limit; otherwise the DRG will be omitted from that bus, and next higher loss bus is chosen, and voltages are checked for acceptable limit again until the optimum location is found.

In 2010, Hung et al. developed a comprehensive analytical expression based on an improvement to the method proposed by Acharya et al. [15] in 2006, which was limited to only one DRG type, extended to find the optimum sizes and optimal location of various types of DRG. Authors considered four major types of DRG based, which include DRG capable of delivering real power only, DRG capable of delivering both real and reactive power, DRG capable of delivering real power and absorbing reactive power, and DRG capable of delivering reactive power only [17]. Hosseini and Kazemzadeh [20] and Hung and Mithulanantha [19] also proposed an improved analytical formulation with the consideration of the power factor for single DRG placement in order to minimize power losses.

2.3. Optimal Power Flow

In 2005, Harrison et al. implemented Optimal Power Flow (OPF) considering 'reverse load-ability' approach to maximize the capacity of DRG and identify any available headroom in the system within the imposed thermal and voltage constraints. The

modelling technique commonly uses the steady-state DRGs as negative load [25]. The objective function is as follows:

$$f(\psi)=\sum_{i=1}^{n}-C_i\times MW_i^0(1-\psi_i) \tag{8}$$

where ψ is capacity adjustment factor, MW^0 is initial active power capacity of DRGs in pu, C is capacity value in per unit megawatt of DRG capacity, i is DRG bus index, and n is number of buses available for capacity addition.

Vovos et al. dealt with generating the capacity allocation, considering additional fault level constraints imposed by protection equipment such as switchgear. An iterative process would allocate new capacity using OPF mechanisms and readjust the capacity to bring fault currents within the specifications of switchgear [28,29].

Gautam and Mithulananthan [24] formulated the problem of optimal placement, including size, with two distinct objective functions, namely social welfare maximization and profit maximization. Social welfare is defined as the difference between the total benefit to consumers, minus the total cost of production [101]. The objective function associated with social welfare has been formulated as the quadratic benefit curve submitted by the buyer (DISCO), ($B_i(P_{Di})$ minus quadratic bid curve supplied by seller (GENCO), $C_i(P_{Di})$ minus the quadratic cost function supplied by DRG owner $C(P_{DGi})$:

$$f=\sum_{i=1}^{N}(B_i(P_{Di})-C_i(P_{Di})-C(P_{DGi})) \tag{9}$$

The profit maximization is formulated as follows:

$$profit_i=\lambda_i\times(P_{DGi})-C(P_{DGi}) \tag{10}$$

where P_{DGi} is the DRG size at node i; λ_i is the locational marginal price (LMP) at node i after placing DRG; $C(P_{DGi})=a_{DGi}+b_{DGi}(P_{DGi})+c_{DGi}(P_{DGi})^2$ is the cost characteristic of DRG at node i. In this method, the traditional OPF algorithm for cost minimization is modified to incorporate the demand bids, in addition to the generation bids. The candidate locations for DRG placement are identified based on LMP, which is determined as the Lagrangian Multiplier of the power balance equation in OPF. The base case OPF based on social welfare maximizing algorithm is used to evaluate the generation dispatch, demand and prices for each of the nodes. The nodal prices obtained are used as indicators to identify the candidate nodes for DRG placement. The placement is intended to meet the demand at a lower price by provide a scenario of variety of DRGs.

In a work published in 2009, Jabr et al. presented an ordinal optimization (OO) method, which aims for loss minimization and DRG capacity maximization in siting and sizing of DRG. The confidence in the OO solution to solve complex problems is set mainly by two parameters; α that specifies the percentage of top designs and P that is the probability level, which at least one of the sampled designs belongs to the top α percentage. The OO approach can be easily implemented by using the existing OPF software [102]. Algarni and Bhattacharya [21] integrated the goodness factors of DRG units directly into the distribution system operation model, based on the OPF framework for incremental contribution of DRG unit to active and reactive power losses, termed as incremental loss indices.

Dent et al. [23] assessed the maximization of total generation under network security constraints using an OPF model which was solved by gradually adding limited numbers of line outage contingencies, until a solution to the complete problem is obtained. The limit on the number of contingencies added reduced the size of the optimization problems encountered. Moreover, varying the limit provides a highly efficient means of searching for multiple local optimal of the nonlinear optimization problem. Apart from the above OPF-based method, OPF also has been used by authors in [22] for evaluating the maximum capacity of variable DRG. Ochoa et al. proposed a multi period AC OPF to determine the optimal accommodation of renewable DRG, which aims to minimize the system energy losses. The algorithm is also applied to evaluate the maximum capacity of new variable DRG which is able to be connected in a distribution network when active network management control strategies are in place. The active network management schemes embedded into the OPF include coordinated voltage control, adaptive power factor and energy curtailment [26,27].

2.4. Mixed Integer Nonlinear Programming

Mixed Integer Nonlinear Programming (MINLP) refers to mathematical programming with continuous and discrete variables and nonlinearities in the objective function and constraints. In 2005, El-Khattam et al. proposed an integrated model for solving the distribution system planning problem by implementing DRG as an attractive option in distribution utility's territories. The total investment objective function is based on the supply-chain model formulation. It aims to minimize the investment and operating costs of DRG, payments toward purchasing the required extra power by the DISCO, total payments toward compensating for system losses along the planning period, as well as alternative costs according to the available different scenarios. The DISCO may have the following alternatives to serve its demand growth [31].

(i) Scenario A: Purchasing the required extra power from the main grid and pumping it to its distribution network through its junction substation with main grid.
(ii) Scenario B: Purchasing the extra power from an existing inter tie and delivering it to its distribution network territory.
(iii) Investing in DRG as an alternative for solving the distribution system planning (DSP) problem without the need for feeder upgrading.

The objective function is as follows [31]:

$$\begin{aligned}J=&\sum_{i=1}^{N}C_{fi}\left(S_{DGi}^{Max}+BK\right)\sigma_{DGi}+8760\sum_{t=1}^{T}\sum_{i=1}^{M}\beta^tC_{ri}S_{DGi}\\&+8760\sum_{t=1}^{T}\beta^t\sum_{i=1}^{TN}M\sum_{j=1}\frac{\Delta V_{ij}^2}{|Z_{ij}|}\cdot pf\cdot C_e\\&+\text{Cost of Scenario A or}+\text{Cost of Scenario B}\end{aligned} \tag{11}$$

where

Cost of Scenario-A is as follows:

$$C_A=\sum_{i=1}^{SS}\sum_{u=1}^{TU}C_{i,u}\sigma_{i,u}+\sum_{i=1}^{TN}\sum_{j=1}^{M}C_{ij}\sigma_{ij}+8760\sum_{t=1}^{T}\beta^tpfC_eS_{i,u}\sigma_{i,u} \tag{12}$$

Cost of Scenario-B is as follows:

$$C_B=\sum_{i=1}^{TN}\sum_{j=1}^{M}C_{ij}\sigma_{ij}+8760\sum_{t=1}^{T}\beta^t\sum_{i=1}^{TU}pfC_{\text{int}}(S_{\text{int}})S_{\text{int}}\sigma_{\text{int}}(S_{\text{int}}) \tag{13}$$

and

$$\beta^t=1(1+d)^t \tag{14}$$

In the above formulation the factors such as backup DRG unit capacity(BK), discount rate (d), investment cost (C_f), operating cost (C_r), electricity market price (C_e), cost of feeder (C_{ij}), cost of transformer ($C_{i,u}$), intertie power cost (C_{int}), number of load buses (M), power generated from DRG (S_{DG}), power imported by intertie (S_{int}), transformer u in substation i dispatch power ($S_{i,u}$), number of substation (SS), incremental time interval (t), horizon planning

year (T), total number of buses (TN), total number of substation transformers (TU), feeder segment impedance ($|Z_{ij}|$), system power factor (pf), DRG binary decision variable (σ_{DG}), feeder i to j binary decision variable (σ_{ij}) transformer u in substation i binary decision variable ($\sigma_{i,u}$), intertie binary decision variable (σ_{int}), DRG capacity limit $\left(S_{DGi}^{Max}\right)$ are considered.

The proposed model integrates comprehensive optimization model and planner's experience to achieve optimal sizing and siting of distributed generation. In this model, binary decision variables are employed in the General Algebraic Modelling System (GAMS) [103] where unity or zero decision variables would mean to invest or not to invest, respectively, to provide accurate planning decisions.

Subsequently, in 2010, Kumar and Gao [32] used MINLP to determine the optimal location and number of DRGs in the pool as well as the hybrid electricity market. The main contribution in this work is: (i) to find the optimal location of DRG based on real power nodal price and real power loss sensitivity index as an economic and operational criterion; (ii) to determine optimal location and optimal number of distributed generators in the identified zone based on the Mixed Integer Nonlinear Programming based approach; and (iii) to find the impact of demand variation for nodal price variation, fuel cost and real power loss without and with DRG. The optimization problem has been formulated in GAMS using SNOPT solver [103]. MATLAB and GAMS interfacings have been used to solve load flow at base case to obtain load flow data and other parameters required for modelling algebraic equation in GAMS [104].

Atwa et al. proposed a probabilistic-based planning technique that combines all possible operating conditions of the renewable DRG units (i.e. wind-based DRG, solar DRG, and biomass DRG) with their probabilities. The problem was formulated as MINLP, considering the uncertainty associated with renewable DRG sources as well as the hourly variations in the load profile. The planning problem comes with an objective function for determining the optimal fuel mix of various types of renewable DRG units in order to minimize the annual energy losses without violating the system constraints. The constraints include the voltage limits, the feeders' capacity, the maximum penetration limit, and the discrete size of the available DRG units [30].

A two-stage MINLP based methodology was proposed by Pokar et al. for DRG placement. The method comes with an objective function to minimize the cost and maximize the total system benefits (TSB). Optimal placement and size are obtained from the total cost minimization mathematical problem, which is solved in the first stage. It shows that there are an optimal location and size for each DRG cost characteristic and for each investment payback time. Consequently, the second stage solves the optimal DRG investment payback time results from the TSB maximization problem. The various DRG technologies include renewable resources like wind and photovoltaic to give the system deciders some choices, which offer the opportunity of selecting the right energy solution at the right location [33].

3. Artificial Intelligent optimization techniques for distributed renewable generation placement

Artificial Intelligent (AI) is commonly defined as the science and engineering of making intelligent machines, especially intelligent computer programs [8]. This section covers a wide range of AI techniques such as Evolutionary Algorithm [34–54], Simulated Annealing [55–57], Differential Evolution [58–63], Particle Swarm Optimization [64–70], Fuzzy Systems [71,72] and Tabu Search [73,74], which have been applied in most optimization problems as well as DRG optimal placement. The applications and goals of these techniques varieties of techniques owe to their great potentials to optimize technical and economical DRG challenges. The fundamental to these techniques are considered below.

3.1. Evolutionary Algorithm

An Evolutionary Algorithm (EA) is meta-heuristic population-based optimization process and converge to the global optimum solution with probability of one by a finite number of evolution steps performed on a finite set of possible solutions [105,106]. EA is a subset of evolutionary computation, which includes Evolutionary Programming (EP), Evolutionary Strategy (ES), and Genetic Algorithm (GA) for optimization based on natural selection: crossover, mutation, recombination, reproduction and selection operators on the population of individuals to perform the search.

Crossover involves choosing a random position in the two strings and swapping the bits that occur after this position; mutation randomly perturbs a candidate solution; recombination randomly mixes their parts to form a novel solution; reproduction replicates the most successful solutions found within a population; whereas selection purges poor solutions from a population. The population is randomly created at the start of the search. Fitness is used to select individuals from the current generation to advance into the next generation. These individuals are recombined and possibly mutated to form the next generation. This process is continued until there is no change in the best individual in the population [107].

The EP is introduced first, and followed by ES and GA [105]. The feasibility to solve efficiently the optimal siting and sizing of DRGs by implementing GA was demonstrated in [45]. GA is a searching and optimization method based on a model of evolution adaptation in nature. It is a very powerful search algorithm and is different from other conventional search algorithms. GA does not need derivatives or other auxiliary knowledge. GA works with a population of individuals and each individual stands for a solution. The quality of a solution is evaluated from its fitness, which is calculated by using fitness function. In case of DRG placement, this fitness is evaluated based on minimizing real power losses, to reduce investments and operational costs, and providing optimal size [108].

An improved Hereford Ranch Algorithm (HRA) was implemented in 1998 with single objective function to minimize the active power loss, and compared with second-order method and classical GA. From the various test results, HRA indicates superior performance over the conventional ones [40]. An EP based methodology has been developed and presented by Khatod et al. for finding the optimal locations of photovoltaic arrays and wind turbine generators in a radial distribution system [51]. The active energy loss was minimized, considering the constraints on bus voltages, line loadings, number of DRGs to be placed and dispatched wind power. Various authors in [42,44,46,48,49] implemented GA to handle single objective, which minimize the total real power losses in the distribution network.

Teng et al. [50], Borges et al. [35] and Shaaban et al. [54] proposed a strategic DRG placement method by implementing GA [35,50,54]. The fitness evaluation function that drives the GA to the solution is derived as a benefit/cost relation, where the benefit is measured from the reduction of electrical losses, and the cost is dependent on investment and installation. GA has also been used by Borges et al. to evaluate the DRG impact on reliability, losses and voltage profile along with DRG planning [35]. Moreover, in 2012, Shaaban et al. [54] took into consideration about the uncertainty and variability associated with the output power of renewable DRG as well as the load variability.

GA has been used by many authors to handle multi-objective (MO) in DRG placement [34,37,38,47,53]. In 2005, Celli et al. proposed a MO formulation for the siting and sizing of DRG resources into existing distribution networks. The methodology objective was achieved by minimizing different functions, which is expressed as

$$Min\ C(X(U)) = Min[C_u, C_L, C_{ENS}, C_E] \tag{15}$$

where X(U) is a power flow solution calculated as function of vector U, which stores the data about the location and the size of generator. C_u is cost of network upgrading, C_L is cost of energy loss, C_{ENS} is cost of energy not supplied, C_E is cost of purchased energy. The implemented technique is based on GA and an ε-constrained method that allows obtaining a set of non-inferior solutions [37].

Carpinelli et al. [36] extended the MO approach in order to include uncertainties in DRG energy production. Each possible future is formulated as a scenario [109]. The mathematical formulation of objective function is formed with three objectives as follows:

$$Min\ C(X(U)) = Min[F_1, F_2, F_3] \tag{16}$$

where F_1 is cost of energy loss, F_2 is voltage profile, and F_3 is power quality. Subsequently, a "double trade-off method" is used. In the first trade-off, by using a MO ε-constrained technique, allows DRG siting and sizing solutions for all the scenarios considered; such as being associated to a different set of wind speed at all the possible locations; the second one allows isolating the most robust solutions. In this way, the planner is completely free to drive the optimization in a certain direction without losing objectivity and generality [36].

In 2007, Haesen et al. proposed a robust MO planning methodology for the integration of stochastic generators in distribution grids. This approach utilizes the Strength Pareto Evolutionary Algorithm (SPEA) algorithm, a predecessor of the SPEA2 algorithm [39]. It was updated to the SPEA2 algorithm in 2009 by Rodriguez et al., extended to include the analysis of controllable DER units and enhanced to take account of objectives that reflect environmental impact and voltage quality [34]. Another MO programming approach based on Non-dominated Sorting Genetic Algorithm (NSGA) was applied by Ochoa et al. to find the best configuration that maximizes the integration of distributed wind power generation while satisfying voltage and thermal limit [43]. Kumar et al. [41] in 2010 proposed the DRG integration approach with MO model implemented for quick restoration and the reduction of additional power demand under cold load pickup using GA. In 2011, Moeini-Aghtaie et al. [52] implemented NSGA-II to minimize the total costs, total losses, and improve system reliability in the distribution system.

3.2. Simulated Annealing

Simulated Annealing (SA) is a process in which the optimization problem is simulated through an annealing process. It has the ability of escaping local minima by incorporating a probability function in accepting or rejecting new solutions. SA was introduced by Kirkpatrick, Gelatt, and Vecchi in 1983 [110]. Due to its implementation together with simplicity and good results, its use has been growing since mid-80s [111]. The initial temperature and cooling procedure are of paramount importance for the good use of SA. The algorithm is based on initialization, perturbation, cooling schedule, and acceptance probability to perform the search.

Sutthibun and Bhasaputra [56] presented a model to determine the optimal location and size of DRG in order to minimize the real power loss (P_L), emission (E_{pg}), and the contingency in terms of severity index (SI) while being subjected to power balance constraint and power generation limit using SA as an optimization tool. The MO function (F) is the weighted sum of individual objective, expressed as follows:

$$F = w_1 P_L + w_2 E_{pg} + w_3 SI \tag{17}$$

where w_1, w_2, and w_3 are weight factors whose values are between 0.2 and 0.6 with condition $w_1 + w_2 + w_3 = 1$.

Another MO optimization model for use to determine the optimal sizing and locating DRG was implemented by Aly et al. [57] for cost minimization, which was achieved via the minimization of system losses, complex power acquired from DRG, and the number of DRG connected. In 2012, Ghadimi and Ghadimi [55] proposed SA in order to minimize power losses for sizing and sitting of DRG and capacitor banks in the distribution network.

3.3. Differential Evolution

Differential Evolution (DE) developed by Storn and Price [112] is a simple yet powerful population based, stochastic function minimizer and has been found efficient and effective to solve various natures of engineering problems [113–116]. DE algorithm is a population-based algorithm like GA, using similar operators; crossover, mutation and selection. DE is used to solve the optimization problem by sampling the objective function at multiple randomly chosen initial points. Pre-set parameter bounds define the region from which 'M' vectors in this initial population are chosen. DE generates new solution points in 'D' dimensional space that are perturbations of existing points, by applying three fundamental operators explained below.

i. Mutation: DE mutates and recombines the population to produce a population of 'M' trial vectors. Differential mutation adds a scaled, randomly sampled, the vector difference to a third vector as follows:

$$V_i^{(k)} = X_{base}^{(k)} + \sigma\left(X_p^{(k)} - X_q^{(k)}\right) \tag{18}$$

where σ is known as scale factor and usually lies in the range [0, 1], $X_p^{(k)}$ and $X_q^{(k)}$ are two randomly selected vectors ($p \neq q$); $X_{base}^{(k)}$ is known as base vector; $V_i^{(k)}$is a mutant vector; the base vector index 'base' may be determined in various ways. This may be a randomly chosen vector ($base \neq p \neq q$).

ii. Crossover: DE employs a uniform crossover strategy. The crossover generates trial vectors, $t_{i,j}^{(k)}$ as follows.

$$t_{i,j}^{(k)} = \begin{cases} v_{i,j}^{(k)} & \text{if } (rand_j \leq C_r \text{ or } j = j_{rand}) \\ x_{i,j}^{(k)} & \text{otherwise} \end{cases} \tag{19}$$

where C_r is crossover probability which lies in the range [0, 1], defined by the user which controls the number of parameter values copied from the mutant. $rand_j$ is the jth evaluation of a uniform random number generator with outcome [0, 1]. j_{rand} is randomly chosen index, which ensures $t_{i,j}^{(k)}$ get at least one parameter from $v_{i,j}^{(k)}$.

iii. Selection: Objective function is evaluated for target vector $f\left(t_i^{(k)}\right)$, and trial vector $f\left(X_i^{(k)}\right)$; trial vector is selected if it provides better value of the function than the target vector as follows:

$$X_i^{(k+1)} = \begin{cases} t_i^{(k)} & \text{if } f\left(t_i^{(k)}\right) \leq f\left(X_i^{(k)}\right) \\ X_i^{(k)} & \text{otherwise} \end{cases} \tag{20}$$

In a work publish in 2010, Hejazi et al. [63] presented DE for optimal allocation of distributed generation in distribution networks considering various technical and economic aspects of the

problem and formulate multi-objective function, which include the cost of network upgrading, cost of purchased energy, cost of energy losses, total voltage deviation and total capacity release. Estabragh and Mohammadian [62] also presented DE for finding the best location of DRG to reach the best condition of voltage stability security margin and power losses. Load ability limit is formulated as the voltage stability index for security assessment in nonlinear optimization problem.

Various authors [58–60] also proposed DE for the placement of single DRG unit in electrical distribution systems to reduce the power losses. Abbagana et al. [59] considered two DRG units with three different types of generation in the DRG planning methodology. In 2012, Arya et al. [61] proposed a technique to quantify the technical benefits with use of sensitivity approaches to decide the appropriate location of wind turbine DRG with induction generator, and determination of their optimum capacities by using DE to minimize transmission losses. Incremental voltage sensitivity aspect was also considered, which accounted for voltage stability consideration.

3.4. Particle Swarm Optimization

Particle Swarm Optimization (PSO) is a population based stochastic optimization technique developed by Dr. Eberhart and Dr. Kennedy in 1995, inspired by social behaviour of bird flocking or fish schooling [117]. The PSO, as an optimization tool, provides a population-based search procedure in which individuals called particles change their position (state) with time. In a PSO system, particles fly around in a multidimensional search space. During flight, each particle adjusts its position according to its own experience (this value is called L_{best}), and according to the experience of a neighbouring particle (this value is called G_{best}), made use of the best position encountered by itself and its neighbour [108].

From mathematical point of view, the above procedures for each agent can be stated as following:

$$V^{i+1} = \omega * V^i + C_1 * rand * \left(L_{best} - X^i\right) + C_2 * rand * \left(G_{best} - X^i\right) \tag{21}$$

$$X^{i+1} = V^{i+1} + X^i \tag{22}$$

The weighting function is usually used as follows:

$$\omega = \omega_{max} - \frac{\omega_{max} - \omega_{min}}{Itre_{max}} Itre \tag{23}$$

ω_{min} and ω_{max} are the minimum and maximum weights, respectively. Appropriate values for ω_{min} and ω_{max} are 0.4 and 0.9. *Itre* and $Itre_{max}$ are the current and maximum iteration, respectively. Appropriate value ranges for C_1 and C_2 are [1,2], but 2 is the most appropriate in many cases.

A multi-objective formulation for optimal siting and sizing of DRG resources in distribution systems was proposed by Hajizadeh and Hajizadeh [64] based on PSO and weight method in order to minimize the cost of power losses (C_L) and energy not supplied (C_{ENS}). The fitness function was derived from the objective function as follows:

$$Min\ C = W_1 C_L + W_2 C_{ENS} \tag{24}$$

where,

$$W_1 + W_2 = 1 \tag{25}$$

Lalitha et al. [65] proposed a two-stage methodology for the optimal DRG placement. In the first stage, fuzzy approach was used to find the optimal DRG locations and in the second stage, PSO was used to find the size of the DRGs corresponding to maximum loss reduction. A hybrid objective function was used for the optimal DRG placement by Mohammadi and Nasab [66]. It had two parts of objective function; in first part, the power loss was proposed as an index named Power Loss Reduction Index (*PLRI*) as consideration; in the second part, the effect of DRG on reliability improvement on the system was considered, named as Reliability Improvement Index (*RII*).

In 2011, El-Zonkoly et al. considered a wide range of technical issues, which are active and reactive power losses of the system, the voltage profile, the line loading and the MVA intake by the grid in DRG planning [70]. The PSO technique was implemented by Kansal et al. [69]and Zareiegovar et al. [67] to find the optimal size and optimum location for the placement of DRG in the radial distribution networks by reduction in real power losses and enhancement in voltage profile. Voltage stability was taken into consideration by Zareiegovar et al. [67] as an objective function in DRG planning.

In order to evaluate the influence of DRG on the total real power losses in the power system and to contribute to the DRG impact evaluation vis-à-vis the network fault protection strategies, in 2012, Maciel et al. proposed a multi-objective based PSO (MEPSO) for minimizing the real power loss (*ILp*) and short circuit level (*ISC*3), which are represented through two indices as follows [68]:

$$Min\ ILp = \frac{Loss^{DG}}{Loss^0} \tag{26}$$

$$Min\ ISC3 = \max_{i=1,NN} \left(\frac{I_{SC}abc_i^{DG}}{I_{SC}abc_i^0} \right) \tag{27}$$

where $Loss^{DG}$ is the real power for the network with a given DRG configuration; $Loss^0$ is the total real power loss without DRG; $I_{SC}abc_i^{DG}$ represents the three-phase fault current magnitude in node *i* for the network with a given DRG configuration; $I_{SC}abc_i^0$ stands for the three-phase fault current magnitude in node *i* for the network without DRG; *NN* is the number of nodes.

3.5. Fuzzy System

The concept of Fuzzy System (FZ) was introduced by Zadeh [118] as a formal tool for dealing with uncertainty and soft modelling. The fuzzy set theory is widely being applied in power systems [119]. A fuzzy variable is modelled by utilizing a membership function which assigns a degree of membership to a set. Usually, this degree of membership varies from zero to one.

The data and parameters used in DRG placement are usually derived from various sources with a wide variance in accuracy. For example, load is considered as known and specified in almost all methods, in spite of having a high uncertainty. In addition, electricity market price, cost of DRG, peak power saving, etc. may be subjected to uncertainty to some degree. Therefore, uncertainties due to insufficient information may generate uncertain region of decisions. Consequently, the validity of the results from average values cannot represent the uncertainty level. To account for the uncertainties in the information and goals related to multiple and usually conflicting objectives in DRG placement, the use of fuzzy set theory may play a substantial role in decision-making [107].

In 2006, the multi-objective allocation of resources was implemented by Ekel et al. using Bellman-Zadeh approach as the decision-making in a fuzzy environment. Authors developed corresponding Adaptive Interactive Decision-Making System (AIDMS) base on the Bellman-Zadeh approach [120]. Lalitha et al. and Kumar et al. implemented fuzzy set theory to determine the suitable locations for DRG placement. Two objectives were considered while designing a fuzzy logic for identifying the optimal DRG locations, which were to minimize the real power loss and to maintain voltage within permissible limits. Voltage stability and power loss indices of the distribution system were

modelled into voltage stability index (VSI) and power loss index (PLI) to obtain DRG suitability index (DSI) as output [71,72].

3.6. Tabu Search

Tabu Search (TS) is a heuristic algorithm for guiding the search to find a good solution for a combinatorial problem. It is derived from the works of Glover and Hansen both in 1986 for solving combinatorial optimization problems [121]. It is an efficient combinatorial method that can achieve an optimal or suboptimal solution within a reasonably short time. It does not need many iteration counts to obtain better solution. It can eliminate local minima to search area beyond the local minima. It is based on moves, neighbourhood, tabu list, aspiration, intensification, and diversification. TS has been successfully applied to obtain optimal or sub optimal solutions to problems such as a timetable, a travelling salesman and so on [108].

To apply TS algorithm for solving optimal operation of distribution network, an initial population, which must meet constraints set, is selected randomly. Tabu list is created through a selection of a number of members from an initial population that has minimum objective function. New population is created based on the mutation and recombination rules. Individuals will be ranked in a descending order according to their fitness function. A number of individuals that have the best fitness function are selected into the next population, and the tabu list will be updated and checked for convergence [108].

The TS application for finding the optimal allocation of DRGs from a view point of loss minimization had been illustrated by Nara et al. To simplify the algorithm, the determination algorithm of the allocation of DRGs and the search algorithm of the sizes of DRGs were disconnected, and a decomposition/ coordination technique was introduced to implement TS into the problem [74]. In 2006, Golsan et al. implemented the TS to solve DRG planning problem, including simultaneous DRG, reactive sources and network configuration planning. By solving this problem, the installation locations, sizes and operation of DRG resources and reactive-power sources in selected buses of a distribution system, can be determined, along with tap positions of voltage regulators and network configuration. In the algorithm, various memory structures such as short, intermediate and long-term memories are also been implemented. In this work, forbidden moves are introduced into the tabu lists by recording numbers that correspond exclusively to each forbidden move [73].

4. Possible promising techniques for future use in distributed renewable generation placement

In recent years, there have been numerous meta-heuristic algorithms implemented to solve the DRG planning problem, which consist of Ant Colony System Algorithm (ACSA) [75,76], Artificial Bee Colony Algorithm [77–80], Cuckoo Search [81,82], Firefly Algorithm [83,84], Imperialist Competition Algorithm [85–88] and several kinds of Hybrid System [89–98].

4.1. Ant Colony System Algorithm

One evolutionary method that has recently been considered is the implementation of finding shortest path by ants. Ant Colony algorithms are based on the behaviour of social insects with an exceptional ability to find the shortest paths from the nest to the food sources using a chemical substance called pheromone [122]. The pheromone is the chemical material deposited by the ants, which serves as critical communication media among ants. Ant Colony System Algorithm (ACSA) is the extension of the Ant Colony Optimization (ACO), and it has a better performance than ACO in most engineering applications [123–126]. To select the next path for any ant, a state transition probability is defined as follows.

$$P_{ij} = \frac{(\tau_{ij})^{\alpha}\left(\eta_{ij}\right)^{\beta}}{\sum (\tau_{ij})^{\alpha}\left(\eta_{ij}\right)^{\beta}} \tag{28}$$

where τ_{ij} is intensity of pheromone between nodes i and j; η_{ij} is the factor indicating the relation of the objective function of any problem with the probability of that path; α and β are control parameters for determining the weight of trail intensity and length of path.

In a work published in 2008, Wang et al. developed an optimization procedure based on the ACSA to seek out the optimal re-closer and DRG locations by minimizing a composite reliability index. The reliability is enhanced, and authors suggested that the idea can be extended to the simultaneous placement of both re-closers and DRGs, which are dependent on one another [75]. Sookananta et al. [76] proposed ACSA for the determination of the optimal location and sizing of DRG in radial distribution systems to reduce the overall line losses of the network.

4.2. Artificial Bee Colony Algorithm

Artificial Bee Colony Algorithm (ABCA) is one of the most recently defined algorithms by Dervis Karaboga [127] in 2005, motivated by the intelligent behaviour of honey bees. ABCA uses only common control parameters such as colony size and maximum cycle number. ABCA was initially proposed for numerical optimization [127], and it is then applied for combinatorial [128], unconstrained and constrained optimization problems [129,130]. ABCA employs only three control parameters (population size, maximum cycle number and limit) that are to be predetermined by the user. ABCA is quite simple, flexible and robust [131–133].

In the ABCA system, artificial bees fly around in a multidimensional search space and some (employed and onlooker bees) choose food sources depending on the experience of themselves and their nest mates, and adjust their positions. In order to produce a candidate food position from the old one in memory, the employed bees use the formula as follows [134]:

$$v_{mi} = x_{mi} + \phi_{mi}(x_{mi} - x_{ki}) \tag{29}$$

where x_k is a randomly selected food source, i is a randomly chosen parameter index and ϕ_{mi} is a random number within the range $[-a,a]$. After producing the new food source, v_m, its fitness is calculated and a greedy selection is applied between v_m and x_m. The fitness value of the solution, $fit_m(x_m)$, may be calculated for minimization problems using the following formula [135]:

$$fit_m(x_m) = \begin{cases} \frac{1}{1+f_m(x_m)} & \text{if } f_m(x_m) \geq 0 \\ 1 + abs(f_m(x_m)) & \text{if } f_m(x_m) < 0 \end{cases} \tag{30}$$

where $f_m(x_m)$ is the objective function value of solution x_m.

An artificial onlooker bee chooses a food source depending on the probability value associated with that food source. The value of p_m is calculated as follows [135]:

$$p_m = \frac{fit_m(x_m)}{\sum_{m=1}^{SN} fit_m(x_m)} \tag{31}$$

Scouts fly and choose the food sources randomly without using experience. If the nectar amount of a new source is higher than that of the previous one in their memory, they memorize the new position and forget the previous one. Thus, ABCA system combines local search methods, carried out by employed and onlooker

bees, with global search methods, managed by onlookers and scouts, attempting to balance the exploration and exploitation process [135].

Latitha et al. and Hussain et al. proposed ABCA to solve the DRG placement problem. The objective function was to minimize the total system real power loss subjected to equality and inequality constraints. The validity of the proposed method has been proven from the comparison ABCA with other existing methods, such as AM and PSO. The results showed that ABCA exhibited excellent solution quality, fast convergence characteristics and the potential for solving complex power system problems [78,79]. ABCA was also implemented by Sohi et al. for loss reduction and line capacity improvement in DRG planning problem [80]. In 2011, Abu-Mouti and El-Hawary [77] proposed ABCA to solve the mixed integer nonlinear optimization problem, to determine the optimal DRG location, size, and power factor with the aim of minimize the total system real power.

4.3. Cuckoo Search Algorithm

Cuckoo Search Algorithm (CSA) is an optimization algorithm inspired by the brood parasitism of cuckoo species, which lay their eggs in the nests of other host birds. CSA is proposed by Yang and Deb in 2009 [136], and it has been applied into the engineering optimization problems and shown its promising efficiency. For ease in describing CSA, the three idealized rules are described as follows [137].

(i) At one time, each cuckoo only lays one egg, and leaves it in a randomly chosen nest.
(ii) The algorithm will carry over the best nests with high-quality eggs (solutions) to the next generations.
(iii) A host bird can discover a foreign egg with a probability, $p_a \in [0,1]$ while the number of available host nests is fixed. In this case, the host bird can either abandon its nest and build a completely new nest elsewhere or simply throw the eggs away.

When generating new solutions $x(t+1)$ for a cuckoo i, a Lévy flight is performed:

$$x_i^{(t+1)} = x_i^{(t)} + \alpha \oplus \text{Levy}(\lambda) \tag{32}$$

where $\alpha > 0$ is the step size which should be related to the scales of the problem of interests; in most cases, α can be set to value 1. The above equation is essentially the stochastic equation for random walk, which is a Markov chain whose next location or status only depends on the current location or status, the first term, as in Eq. (32), and the transition is probability, the second term. The product $\oplus$ represents the entry wise multiplication, which is similar to those used in PSO. In terms of exploring the search space, random walk via Lévy flight is more efficient as its step length is much longer in the long run [137].

The random step length of Lévy flight, which fundamentally provides a random walk, is derived from a Lévy distribution with an infinite variance and infinite mean.

$$\text{Levy} \sim u = t^{-\lambda} \tag{33}$$

here, the sequential jumps of a cuckoo fundamentally form a random walk process with a power law step length distribution with a heavy tail. Several new solutions should be generated by the Lévy walkabout in finding the best solution, as this process will speed up the local search. However, a significant fraction of the new solutions should be generated through far field randomization, and whose locations should be far enough from the current best solution, to make sure the system not trapped in a local optimum [136].

In a work presented in 2012, Fard et al. implemented CSA to improve voltage profile and reduce power losses in a prolonged period for two types of the most economical types DRG units, which consist of biomass and solar-thermal [82]. Intelligent building of the distribution network is modelled via non-constant loads connected to the network with the aid of Monte Carlo method. CSA was also applied by Moravej et al. for optimal DRG allocation to reduce power loss and improve voltage profile of the distribution network [81]. The voltage profile which is the main criterion for power quality improvement is expressed by two indices, which are voltage deviations from the target value, which must be minimized, and voltage variations from the base case of network without DRG, which must be maximized.

4.4. Firefly Algorithm

The Firefly Algorithm (FA) is a meta-heuristic algorithm, inspired by the idealized behavior of the flashing characteristics of fireflies. The primary purpose of a firefly's flash is to act as a signal system to attract other fireflies. The idea is to use the concept of flashing characteristics of fireflies to consequently develop firefly-inspired algorithms as the following three rules [138]:

(i) All fireflies are unisex so that one firefly is attracted to other fireflies regardless of their sex.
(ii) Attractiveness is proportional to their brightness, thus for any two flashing fireflies, the less bright one will move towards the brighter one. The attractiveness and brightness will both decrease as their distance increases. If no one is brighter than a particular firefly, it moves randomly.
(iii) The brightness or light intensity of a firefly is affected or determined by the landscape of the objective function to be optimized.

In other words, the brightness can be defined in a similar way as the fitness function in GA [138]. In the FA, there are two important issues of the variation of light intensity and the formulation of the attractiveness. For simplicity, it is assumed that the attractiveness of a firefly is determined from its brightness which in turn is associated with the encoded objective function of the optimization problems. In the FA, there are three important issues: [139]

Attractiveness: The main form of attractiveness function $\beta(r)$can be by any monotonically decreasing functions such as the following generalized form:

$$\beta(r) = \beta_o e^{-\gamma r^m} \quad (m \geq 1) \tag{34}$$

where r is the distance between two fireflies, $\beta(r)$ is the attractiveness at $r=0$ and γ is a fixed light absorption coefficient.

Distance: The distance between any two fireflies i and j at x_i and x_j is the Cartesian distance as follows:

$$r^{ij} = \|x^i - x^j\| = \sqrt{\sum_{k=1}^{d} (x^{i,k} - x^{j,k})^2} \tag{35}$$

where $x_{i,k}$ is the kth component of the ith firefly, x_i, $x_{j,k}$ is the kth component of the j-th firefly, x_j.

Movement: The movement of a firefly, i is attracted to another more attractive (brighter) firefly j, is determined using

$$x^{i+1} = x^i + \beta^o e^{-\gamma r_{ij}^2}\left(x^j - x^i\right) + \alpha(rand - 0.5) \tag{36}$$

where the second term is due to the attraction, while the third term is a randomization with α being the randomization parameter and $rand$ is a random number generator uniformly distributed in range of 0 to 1.

In 2012, Saravanamutthukumaran et al. applied FA to find the optimal allocation of DRG to minimize real and reactive power losses, line loading, short circuit level index, Mega Volt Ampere (MVA) intake by grid, and improve voltage profile for different load models [84]. The load models included in the work consisted of constant load, residential load, commercial load, and industrial load. Sulaiman et al. [83] also presented an application of FA in determining the optimal location and size of DRG in distribution power networks with the aim to minimize real power losses.

4.5. Imperialist Competitive Algorithm

Imperialist Competitive Algorithm (ICA) was proposed by Atashpaz and Lucas [140]. This method is a new socio-politically motivated global search strategy that has recently been introduced for dealing with different optimization tasks. Same as the Evolutionary Algorithms, ICA commences with an initial population of P countries, which are generated randomly within the feasible space. The best countries in the initial population are selected as the imperialists and other counties are known as the colonies of these imperialists. To build initial empires, colonies are divided among imperialists based on each imperialist's power, which is define as normalized cost as follows:

$$C^n = c^n - \max\left(c^i\right) \tag{37}$$

where c_n is the cost of n-th imperialist and C_n is the normalized cost. As a result, the normalized power of each imperialist can be defined as follows:

$$P_n = \left| \frac{c_n}{\sum_{i=1}^{Nimp} c_i} \right| \tag{38}$$

After dividing the colonies among the imperialists, these colonies will start being closed to their empire. The total power of an empire can be determined by expression as follows:

$$Power_n = \mathrm{cost}(imperialists_n) - \xi * mean\mathrm{cost}(colonies\ of\ empires_n) \tag{39}$$

where $Power_n$ is the total power (cost) of the nth empire and ξ is a positive number less than 1 and near to 0. Competition among empires will then occur, which results as an increase as the power of strong empires and decrease as the power of weak ones. Weak empires will lose their power and collapse. Finally, by using the movement of colonies towards their relevant imperialist and also the collapse mechanism, one imperial will exist, which is the optimum solution.

Jahani et al. [88] applied ICA to minimize the total real power losses in the distribution network. ICA was also used by Nejad et al. [87] to minimize the total real power loss and improve voltage profile. In order to maximize the benefits of distribution network operators (DNO), Soroudi and Ehsan [85] proposed ICA in DRG planning problem and considered the sum of active loss reduction and network investment deferral incentives as the objective function to be maximized. The optimal location and size of DRG units within the network are found considering various techno-economic issues, and the objective function is formulated as follows:

$$OF = \mu_1 - \mu_n \tag{40}$$

where

$$\mu_1 = \psi \times \left(Loss^{no\ dg} - \sum_{i=1}^{N_b} P_{i,t}^{net} \right) \tag{41}$$

$$\mu_n = \gamma \times \sum_{i=1}^{N_b} P_i^{dg} \tag{42}$$

ψ is the coefficient of incentive for each MWh reduction of active losses, $Loss^{no\ dg}$ is the active loss when no DRG unit is installed in the network, $P_{i,t}^{net}$ is the net active power injected to bus i, γ is the coefficient of incentive for each MW of installed DRG units, and P_i^{dg} is the active power injected by a DRG in bus i.

In 2012, Rahmatian et al. [86] proposed ICA to determine the capacity and location of DRG by considering the islanding mode of a distribution network including sensitive loads. The distribution system is divided into zones, and each zone should include a DRG unit and sensitive loads. On the other hand, when the load density is high, the zone will be less extensive and enclose fewer numbers of buses. Therefore, the capacity of the installed DRG units will be in an acceptable range for each zone. As a result, sensitive loads are fed more reliably into the islanding mode, and the network losses are reduced.

4.6. Hybrid Intelligent System

Hybrid Intelligent System (HIS) is defined as a combination of methods and techniques from artificial intelligence sub fields, in parallel, to form a new software system. Various types of HIS which include Genetic-Fuzzy (GA-FZ) [90,93], Genetic-Tabu (GA-TS) [89], Genetic-Particle Swarm (GA-PSO) [94], Genetic-Optimal Power Flow (GA-OPF) [91,92,98], Particle Swarm Optimization-Optimal Power Flow (PSO-OPF) [96], and Tabu-Fuzzy (TS-FZ) [95] have been applied in DRG allocation and sizing problems.

4.6.1. Genetic-Fuzzy

Kim et al. presented Genetic-Fuzzy (GA-FZ) method to solve DRG placement for distribution systems. Power loss cost of distribution systems was taken as the objective function, and the number or size of DRGs and deviation of bus voltage were taken as constraints. The original objective function and constraints were transformed into equivalent multi-objectives functions and modelled with fuzzy sets to evaluate their imprecise nature. The authors obtained a global solution of multi-objectives and imprecise information using goal programming and GA, without any transformation for this nonlinear problem to a linear model or other methods [93].

Haghifam et al. proposed a MO model consisting of monetary cost index, operation costs, planning costs, technical risk and economic risk. A fuzzy approach was used in the modelling of load and electricity price uncertainties and related risks. To solve this MO problem, the concept of Pareto optimality, based on Non-dominant Sorting Genetic Algorithm (NSGA-II) [141], was used. The final solution was found using a max–min approach to select the best Pareto-optimal DRG placement solution. The obtained results showed that the proposed DRG placement model was a powerful decision-making tool for risk management in distribution networks with DRG installation and operation [90]. DRG planning problems were also solved using GA-FZ by Akorede et al. [97] to maximize the system loading margin as well as the profit of the DISCO over the planning period. The objective functions are fuzzified into a single multi-objective function, and subsequently solved using genetic algorithm (GA).

4.6.2. Genetic-Tabu Search

A new implementation of a Genetic-Tabu Search (GA-TS) algorithm into the optimal allocation of DRGs in the distribution network had been illustrated by Gandomkar et al. The power

losses, including harmonic power losses were considered as the objective function. The proposed algorithm effectively solved the DRG allocation problem as demonstrated through the study example. A comparison was made between GA-TS, and the GA. GA-TS was found to be much better than GA in terms of solution accuracy and convergence process. The theoretical procedure of the proposed algorithm can be summarized as follows [89].

(i) The variables of GA and TS are initialized.
(ii) An initial population is created by randomly generating a set of feasible solutions (chromosomes).
(iii) Each chromosome is evaluated by running the load flow program to determine the fitness function of each chromosome in the population.
(iv) GA operators are applied to generate new populations as follow: copy the best solution from the current into the new population, using TS algorithm, generate new members in the new population (typically 3–15% of the population size) as neighbours to randomly selected solutions in the current population.
(v) The crossover and mutation operator are applied to produce new populations.
(vi) If the convergence criterion is satisfied, stop. Otherwise, repeat the process from the step of evaluate the fitness of each chromosome.

4.6.3. Genetic-Particle Swarm Optimization

In 2011, Moradi et al. present a novel Genetic-Particle Swarm Optimization (GA-PSO) for determining the optimal location and sizing of DRG on distribution systems. The objective was to minimize network power losses, better voltage regulation and improve the voltage stability within the frame-work of system operation and security constraints in radial distribution systems. The proposed methodology was a searching technique developed for optimal sitting and sizing of DRG. The problem consisted of two parts. The first was the optimal location of DRG, which was solved using GA and the second was the optimal sizing solved in PSO. GA was chosen to play this role because of its attractive quality. The answer obtained from GA solution was used in PSO algorithm to optimize the sizing for DRG. The PSO had fast convergence ability which is a great attractive property for a large iterative and time consuming problem. The interaction between the two algorithms can be summarized as follows [94]:

(i) Time counter is set to 0 and chromosomes, which represent that initial candidates sitting of DRG are generated randomly.
(ii) Each chromosome and optimal sizing of DRG is evaluated using PSO.
(iii) Particle population is initialized, matrix and the size of DRG is modified.
   - The objective values which are the total real power losses, and the voltage profile improvements are modified.
   - Objective function is recorded as the best candidate among the particle and the minimum value as the current overall global best of the group.
   - The velocity (v) and position are updated.
   - The stop criterion is checked; if it is satisfied, then stop.
(iv) The time counter is updated, $t=t+1$.
(v) New population of sitting of DRG is created by repeating GA (selection, crossover and mutation) until the new population is completed.
(vi) Fitness is evaluated using PSO, and time is updated.
(vii) The stop criterion is checked, if it is satisfied, then stop, or else go for time updating.

4.6.4. Genetic-Optimal Power Flow

Harrison et al. had emphasized that GA combined with OPF (GA-OPF) could provide the best combination of sites within a distribution network for connecting a predefined number of DRGs. In doing so, it overcomes known limitations inherent in current available techniques to optimize the DRG capacity. Its use would be to enable DNOs to search the network for the best sites to strategically connect a small number of DRGs among a large number of potential combinations [91,92].

For capacity evaluation using OPF, the linear function is assumed as follows:

$$f_{OPF} = \sum_{g=1}^{n} C_g(P_g) - C_L\left(P_L^{BM} - P_L^{ACT}\right) \tag{43}$$

where $C_g(P_g)$ is the benefit or incentive (£kW^{-1} year^{-1}) of connecting a generator g of capacity P_g, C_L represents the value of the loss incentive as applied to the difference between the actual level of losses P_L^{ACT} and the target losses P_L^{BM}. The GA generates combinations of locations from those available in the network. For each combination of locations, an OPF is performed to define the available capacity and evaluate the objective function. This information is fed back to the GA which searches for the 'DNO optimal' connectable capacity. In doing this the method should deliver the best locations as well as the capacities available for a user-specified number of DRG.

An OPF was proposed by Naderi et al. in 2012 to minimize the capital costs for network upgrading, operation and maintenance costs, and the cost of losses for handling the load growth for the DRG planning horizon [98]. The term "dynamic" is used to refer to the planning over a specific period so that the dynamic distribution system planning is, in fact, proposed, where a year-dependent decision-making variable would be defined into the model. The load duration curve was used to include the way that the customer loads may change. Also, the impact on the electricity market was considered based on a load-dependent electricity price. Moreover, a modified GA was used to find the optimal topology solution.

4.6.5. Particle Swarm Optimization-Optimal Power Flow

A new hybrid method, which employs discrete PSO and OPF, is proposed by Gomez-Gonzalez et al. to connect within a distribution network a predefined number of DRG among a large number of potential combinations. In PSO-OPF, a particle is defined as a combination of DRG locations. The objective function includes loss minimization and DRG capacity maximization at once. In each iteration and for each particle, an OPF is performed, which generates the optimal capacity for DRG unit. This complies with the technical constraints imposed by DISCO and agrees to a value of the objective function. Computer simulation has demonstrated good performance, accuracy, robustness, diversification and intensification of the proposed method in comparison to GA [96].

4.6.6. Tabu-Fuzzy

Ignacio et al. present a new possibility's model by implementing FZ for the MO optimal planning of power distribution networks that seek for the non-dominated MO solutions corresponding to the simultaneous optimization of the fuzzy economic cost, level of fuzzy reliability, and exposure (optimization of robustness) of such networks, using an original and powerful meta-heuristic algorithm based on TS. This Tabu-Fuzzy (TS-FZ) model is used to determine the optimal location and size

of the future feeders and substations in the distribution networks with dimensions significantly larger than in other papers. The model also allows determining the optimal reserve feeders which include the location and size that provide the best distribution network reliability at the lowest cost for a given level of robustness [95].

5. Conclusions

This paper provides a timely review of the state-of-the-art of optimal DRG placement techniques. Each method has been utilized to solve problems with various and limited objectives and constraints. Fig. 4 shows a summary of citation, a summary of potential researches related to DRG planning, clearly indicating the increasing trend over recent years. The techniques implemented in this literature of DRG allocation are summarized in Tables 2 and 3, leading to the following conclusions:

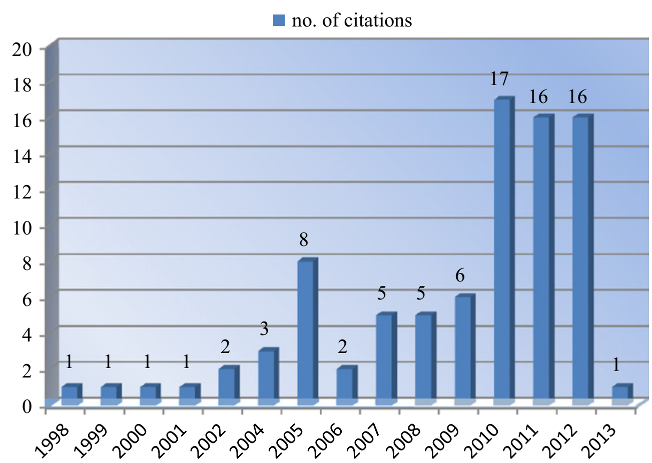

Fig. 4. Summary of citation of researches on DRG planning in this article.

(i) The analytical techniques have the best precision factor while power flow and Artificial Intelligent methods have next advance levels. Moreover, the process speed in the Artificial Intelligent techniques is slower, compared to the Optimum Power Flow and Analytical Methods. However, the consideration of nonlinear algorithms and integer variables will make the conventional method be possibly less robust and the running time would be much longer, while Artificial Intelligent methods can address the integer variable very well.

(ii) Genetic Algorithm is competent of getting a solution near global minima computationally intensive. The Ant Colony System Algorithm, Artificial Bee Colony, Cuckoo Search and other future promising algorithms still have not been paid much attention by researchers. Fuzzy set theory is suitable to model the uncertainties in objective function, constraints, electricity price, generation, and load for better compromised solution. Tabu Search is an efficient combinatorial method which can be used to achieve an optimal or sub optimal solution within a reasonably short duration.

(iii) Artificial Intelligent methods are more heuristic than conventional techniques, which needs further improvement and investigation regarding performance on various larger power systems with their improved versions, such as the Hybrid Intelligent Systems.

In practice, the main problem is the complexity of the power system. Many constraints should be considered simultaneously such as power loss, reliability, load factors, voltage profile, voltage

Table 2
Brief comparison on the advantages and disadvantages of main approaches applied for the DRG placement.

DRG placement method	Advantages	Disadvantages	**Reference**
2/3 Rule	Simple and easy to use approximate technique	Not suitable applied directly to non-uniform load network systems	[14]
Analytical Method	Easy to implement, high precision factor, computational time efficiency	Fewer literature examples, lacks robustness, only can consider single objective and single DRG at a time	[15–20]
Optimal Power Flow	Easy to find literature examples, high precision factor, computational time efficiency	Problem formulated in "closed" manner, hard to include different aspect into calculation	[21–29]
Mixed Integer Nonlinear Programming	High precision factor, computational time efficiency	Hard to implement and understand	[30–33]
Evolutionary Algorithm	Efficient performance for finding the global optimum, easy to find literature examples	Relatively harder to code, premature convergence, possibility of trapping into local optima, lower precision factor	[34–54]
Simulated Annealing	Ease of implementation, ability to provide reasonably good solutions for many combinatorial problems, robustness	Relatively lower performance for finding the global optimum, large computational time	[55–57]
Differential Evolution	Fewer parameters setting, capable of handling complex optimization problems	Unstable convergence, possibility of trapping into local optima	[58–63]
Particle Swarm Optimization	Easy to code with few equations, easy to find literature examples	Relatively lower performance for finding the global optimum, fewer literature examples	[64–70]
Fuzzy System	Easy to understand and suitable to model uncertainties for better compromised solution	Fewer literature examples	[71, 72]
Tabu Search	Efficient performance for achieve an optimal or sub optimal solution, capable to escape from local minimum	Relatively harder to code due to many parameters to be tuned, lower precision factor	[73, 74]
Ant Colony Search Algorithm	Easy to understand and code	Probability distribution changes by iteration, uncertain time to convergence, fewer literature examples	[75,76]
Artificial Bee Colony Algorithm	Capable of handling complex optimization problems, easy to code	Fewer literature examples	[77–80]
Cuckoo Search	Easy to code, less parameters setting	Slow convergence, fewer literature examples	[81,82]
Firefly Algorithm	Easy to understand and code	Slow convergence, fewer literature examples	[83,84]
Imperialist Competition Algorithm	Capable of handling complex optimization problems	Relatively harder to code due to many parameters to be tuned, fewer literature examples	[85–88]
Hybrid Intelligent System	Efficient performance for finding the global optimum, capable of handling complex optimization problems	Relatively harder to code, fever literature examples	[89–98]

Table 3
Summary of DRG allocation methods.

Author(s)	Year	Methods	Objective(s)	Power system, load level	DRG location	References
H.L. Willis	2000	2/3 Rule	Minimize power losses and voltage impact	None	Single	[14]
C. Wang et al.	2004	AM	Minimize real power losses	6 and 30 bus system, Time-varying and Time-invariant load	Single	[18]
N. Acharya et al.	2005	AM	Minimize real power losses	30, 33, and 69 bus system, One load level	Single	[15]
T. Gözel et al.	2009	AM	Minimize real power losses	12 bus system, One load level	Single	[16]
D.Q. Hung et al.	2010	AM	Minimize power losses	16, 33, and 69 bus system, One load level	Single (Mix sources)	[17]
R.K. Hosseini et al.	2011	AM	Minimize power losses	33 and 69 bus system, One load level	Single (consider power factor)	[20]
D.Q. Hung et al.	2012	AM	Minimize power losses	33 bus system, One load level	Single (consider power factor)	[19]
G.P. Harrison et al.	2005	OPF	Maximize capacity of DRG	9 bus system, Multi load level	Multiple	[25]
P.N. Vovos et al.	2005	OPF	Maximize the new generation capacities and energy export	12 bus system, One load level	Single	[28]
P.N. Vovos et al.	2005	OPF	Maximize the new generation capacities and energy export	12 bus system, One load level	Multiple	[29]
D. Gautam et al.	2007	OPF	Maximize social welfare and profit	9 bus system, One load level	Single	[24]
A.A.S. Algarni et al.	2009	OPF	For disco owned: Minimize cost of active and reactive power from substation bus, cost of active and reactive power from DRG, and cost of DRG active and reactive power in conjunction with goodness factor For investor owned: Minimize cost of active and reactive power from substation bus, cost of energy purchased from DRG, and cost of DRG active and reactive power in conjunction with goodness factor	18 and 69 bus system, One load level	Multiple	[21]
C.J. Dent et al.	2010	OPF	Maximize total DRG active power capacity	73 bus system of consists of three area which contains 24 buses each. One load level.	Multiple	[23]
C.J. Dent et al.	2010	OPF	Maximize total DRG active power capacity	10 bus system of U.K. distribution System. One load level	Multiple	[22]
L.F. Ochoa et al.	2010	OPF	Evaluate the maximum capacity for variable (renewable) generation under a range of ANM schemes including coordinated voltage control, adaptive power factor control, and energy curtailment.	16 and 61 bus system of U.K. generic distribution system. Multi load level	Single and multiple	[26]
L.F. Ochoa et al.	2011	OPF	Minimize energy losses	61 bus system of U.K. generic distribution system. Multi load level	Multiple	[27]
W. El-Khattam et al.	2005	MINLP	Minimize cost of investment and operation of DRGs, losses cost and cost of purchasing power by DISCO from grid	9 bus system. One load level	Multiple	[31]
A. Kumar et al.	2010	MINLP	Minimize total fuel cost of DRG and conventional generators, and line losses	24 bus system. One load level	Single and multiple	[32]
Y.M. Atwa et al.	2010	MINLP	Minimize annual energy losses	42 bus system. Variable load level	Multiple (Mix sources)	[30]
S. Pokar et al.	2010	MINLP	Minimize cost and maximize total system benefit	30 bus test system. Multi load level	Multiple	[33]
J.O. Kim et al.	1998	HRA	Minimize real power losses	6, 14, and 30 bus system. One load level	Multiple	[40]
D.K. Khatod et al.	2012	EP	Minimize active energy losses	69 bus system. One load level	Multiple	[51]
A. Silvestri et al.	1999	GA	Minimize sum of cost of power losses, network reinforcement and energy production cost	43 and 93 bus systems. One load level	Single	[45]
J-H. Teng et al.	2002	GA	Maximize the DRG benefit cost ratio	40 bus system. One load level	Multiple	[50]
N. Mithulananthan et al.	2004	GA	Minimizing real power losses	30 bus system. One load level	Single	[42]
D.H. Popovic et al.	2005	GA	Maximize DRG capacity	75 bus system. Multi load level	Multiple	[44]
C.L.T. Borges et al.	2006	GA	Maximize the DRG benefit cost ratio	39 bus system. One load level	Single	[35]
D. Singh et al.	2007	GA	Minimize real power losses	16, 37, and 75 bus system. Multi load level	Single	[46]
R.K. Singh et al.	2009	GA	Minimize real power losses		Single	[48]

Table 3 (*continued*)

Author(s)	Year	Methods	Objective(s)	Power system, load level	DRG location	References
				30 bus system. Multi load level		
R.K. Singh et al.	2009	GA	Minimize performance indices include real power losses, reactive power losses, line power flow, and node voltage	16 and 37 bus system. Constant, residential, industrial and commercial load models	Single	[49]
D. Singh et al.	2009	GA	Minimize performance indices include real power losses, reactive power losses, line power flow, and node voltage	16 and 37 bus system. Constant, residential, industrial and commercial load models	Single	[47]
A.A.A. El-Ela et al.	2010	GA	Minimize multi-objective function includes voltage profile improvement, spinning reserve increase, power flow reduction in critical lines and total line losses reduction	8 bus system. One load level	Single	[38]
V. Kumar et al.	2010	GA	Minimize multi-objective function includes load to be curtailed, bus voltage violation, branch current violation, substation transformer over loading	33 bus system. One load level	Multiple	[41]
M.F. Shaaban et al.	2011	GA	Minimize cost of energy losses and cost of interruption	38 bus system. Mixed load level	Multiple	[54]
N.C. Yang et al.	2012	Dual GA	Maximize allowable DRG capacity within short circuit capacity limits	Taipower radial network	Multiple	[53]
G. Celli et al.	2005	GA and ε-constrained Method	Minimize multi-objective function include cost of network upgrading, energy purchased, energy losses and energy not supplied	78 bus system. Peak load with constant growth rate	Multiple	[37]
G. Carpinelli et al.	2005	GA and ε-constrained method	Minimize multi-objective function include cost of energy losses, improvement in voltage quality and harmonic distortion	18 bus system. Peak load with constant growth rate	Single	[36]
E. Haesen et al.	2007	SPEA	Minimize total line losses, main grid energy flow, DRG installation costs and gas distribution grid investments	30 bus system. One load level	Multiple	[39]
A.A. Alarcon-Rodriguez et al.	2009	SPEA2	Minimize multi-objective function includes annual DRG dispatched energy for local ancillary, annual DRG curtailed energy, CO_2 emission, and voltage quality index	UKGDS radial network. Stochastic load	Single	[34]
L.F. Ochoa et al.	2008	NSGA	Multi-objective functions are to maximize energy export, minimize real power losses, and minimize single phase short circuit level	33 bus system. Time varying load	Single (variable)	[43]
M. Moeini-Aghtaie et al.	2011	NSGA-II	Minimize total costs, total losses, and improve system reliability	27 bus system. One load level	Multiple	[52]
T. Sutthibun et al.	2010	SA	Minimize multi-objective function includes power loss, emission, and severity index	33 bus system. One load level	Multiple	[56]
A.I. Aly et al.	2010	SA	Minimize power losses, complex power acquired from DRG, and the number of DRG connected	68 bus system. One load level	Multiple	[57]
N. Ghadimi et al.	2012	SA	Minimize power losses	33 bus system. One load level	Multiple	[55]
H.A. Hejazi et al.	2010	DE	Multi-objective functions include minimize cost of network upgrading, cost of purchased energy, cost of energy losses, total voltage deviation and total capacity release	37 bus system. One load level	Multiple	[63]
M.R. Estabragh et al.	2011	DE	Minimize power losses and maximize load ability limit	14 bus system. One load level	Multiple	[62]
J. Gunda et al.	2011	DE	Minimize power losses	Indian Electricity Board 25 bus system. One load level	Multiple	[58]
I. Hussain et al.	2012	DE	Minimize power losses	33 bus system. One load level	Multiple	[60]
M. Abbagana et al.	2012	DE	Minimize power losses	33 bus system. One load level	Multiple	[59]
L.D. Arya et al.	2012	DE	Minimize power losses	6 and 30 bus system. One load level	Multiple	[61]
A. Hajizadeh et al.	2008	PSO	Minimize the cost of power losses and energy not supplied	33 bus system. One load level	Multiple	[64]
M.P. Lalitha et al.	2010	PSO	Minimize real power losses	33 bus system. One load level	Multiple	[65]
M. Mohammadi et al.	2011	PSO	Minimize real power losses and improve system reliability	12 bus system. One load level	Single	[66]
S. Kansal et al.	2011	PSO	Minimize power losses	33 bus system. One load level	Single	[69]
A.M. El-Zonkoly	2011	PSO	Minimize multi-objectives indices include real power losses, reactive power losses, line loading, short circuit level, and improve voltage profile	38 and IEEE 30 bus system. Constant, residential, industrial and commercial load models	Multiple	[70]
G. Zareiegovar et al.	2012	PSO	Minimize power losses, improve voltage stability, and voltage profile	69 bus system. One load level	Multiple	[67]
R.S. Maciel et al.	2012	MEPSO	Minimize real power losses and short circuit level	34 and 123 bus system. One load level	Multiple	[68]
M. P. Lalitha et al.	2010	FZ	Minimize real power losses	33 bus system. One load level	Multiple	[72]
K. Injeti et al.	2011	FZ	Minimize real power losses and improve the voltage profile	12, 33, and 69 bus system. One load level	Single	[71]

Table 3 (*continued*)

Author(s)	Year	Methods	Objective(s)	Power system, load level	DRG location	References
K. Nara et al.	2001	TS	Minimize real power losses	28 sections and 78 sections. Multi load level	Multiple	[74]
M.E.H. Golshan et al.	2006	TS	Minimize cost function including cost of power losses at peak load time, cost of fuel served for energy losses and the cost of reactive sources	33 and 69 bus system. Peak load and multi load level	Multiple	[73]
L. Wang et al.	2008	ACSA	Optimize multi-objective function consists of SAIFI and SAIDI	39 and 394 bus system. One load level	Multiple	[75]
B. Sookananta et al.	2010	ACSA	Minimize real power losses	12 and 15 bus system. One load level	Single	[76]
M.P. Lalitha et al.	2010	ABCA	Minimize real power losses and improve voltage profile	33 bus system. One load level	Multiple	[78]
F.S. Abu-Mouti et al.	2011	ABCA	Minimize real power losses	69 bus system. One load level	Multiple	[77]
M.F. Sohi et al.	2011	ABCA	Minimize real power losses and improve line capacity	33 bus system. One load level	Multiple	[80]
I. Hussian et al.	2012	ABCA	Minimize real power losses	33 bus system. One load level	Multiple	[79]
M.M. Fard et al.	2012	CSA	Minimize power losses and improve voltage profile	33 bus system. Non-constant load (generated by Monte Carlo)	Multiple	[82]
Z. Moravej et al.	2013	CSA	Minimize real power losses and improve voltage profile	69 bus system. One load level	Multiple	[81]
S. Saravanamutthuku-maran et al.	2012	FA	Minimize multi-objectives indices include real power losses, reactive power losses, line loading, short circuit level, and improve voltage profile	38 bus system. Constant, residential, industrial and commercial load models	Multiple	[84]
M.H. Sulaiman et al.	2012	FA	Minimize real power losses	69 bus system. One load level	Multiple	[83]
R. Jahani et al.	2011	ICA	Minimize real power losses	34 and 69 bus system. One load level	Single	[88]
H.C. Nejad et al.	2011	ICA	Minimize real power losses and improve the voltage profile	33 bus system. One load level	Multiple	[87]
A. Soroudi et al.	2011	ICA	Minimize power losses and maximize network investment deferral incentives	69 bus system. One load level	Multiple	[85]
M. Rahmatian et al.	2012	ICA	Minimize power losses considering the islanding modedistribution network	33 bus system. One load level	Multiple	[86]
K-H. Kim et al.	2002	GA-FZ	Minimize real power losses cost	12 bus system. Multiload level	Multiple	[93]
M-R. Haghifam et al.	2008	GA-FZ	Multi-objective function is in three groups:(i) cost (ii) technical risk (iii) technical risk.Minimize multi-objective function include: (i) Cost of energy losses, investment cost of DRG units; operation and maintenance cost; (ii) substation loading, line loading; voltage. (iii) cost of power purchased from grid, cost of power generated by DRG	9 bus system. Aggregated load level	Multiple	[90]
M.F. Akorede et al.	2010	GA-FZ	Maximize the system loading margin and the profit of the DISCO	6 and 30 bus system	Single	[97]
M. Gandomkar et al.	2007	GA-TS	Minimize power losses	13 and 34 bus system. Multiple load level	Single	[89]
M.H. Moradi et al.	2011	GA-PSO	Minimize network power losses, improve voltage regulation and voltage stability	33 and 69 bus systems. One load level	Single	[94]
G.P. Harrison et al.	2007	GA-OPF	Maximize DRG capacity	69 bus system. One load level	Multiple	[91]
G.P. Harrison et al.	2008	GA-OPF	Maximize incentive to DNO by optimizing DRG capacity and loss reduction	69 bus system. One load level	Multiple	[92]
E. Naderi et al.	2012	GA-OPF	Minimize investment cost, operation and maintenance cost, and cost of power losses	9 bus system. Time-varying load	Multiple	[98]
M. Gomez-Gonzaleza et al.	2012	PSO-OPF	Maximize DRG capacity and loss reduction	30 bus system. One load level	Multiple	[96]
I.J. Ramírez-Rosado et al.	2004	TS-FZ	Minimization of the economic cost, expected nonsupplied energy and exposure	182 bus real system. Multi load level	Multiple	[95]

stability, operational cost, emission of greenhouse gases, and related capacity. These are the main reasons most researchers have divided the problem into limited parts along with imposed constraints and tried to propose their own solutions. However, the systematic principles for DRG placement issue is still an unsolved problem despite many optimization methods have been proposed. In this literature, several popular methods to select the DRG site have been considered along with their potentials and applications. Each methodology has its own features and potential to significantly promote the applicability of DRG in power systems.

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